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# 2D Sound Source Localization on the Binaural Manifold

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## Motivation

Traditional approaches to SSL



$$TDOA = \frac{\|m_1 - s\| - \|m_2 - s\|}{C} \propto \sin(\theta)$$

- Simplified model of sound propagation, based on the system geometry
- Mainly using the time difference of arrival (TDOA)

### Pros:

- Simple and fast method
- Works well in anechoic, clean set-ups

### Cons:

- 1D localization only
- Poor accuracy due to approximations
- Need for external parameters
- Suffers in more complex set ups (ac. head)
- Performances depend on the emitted sound

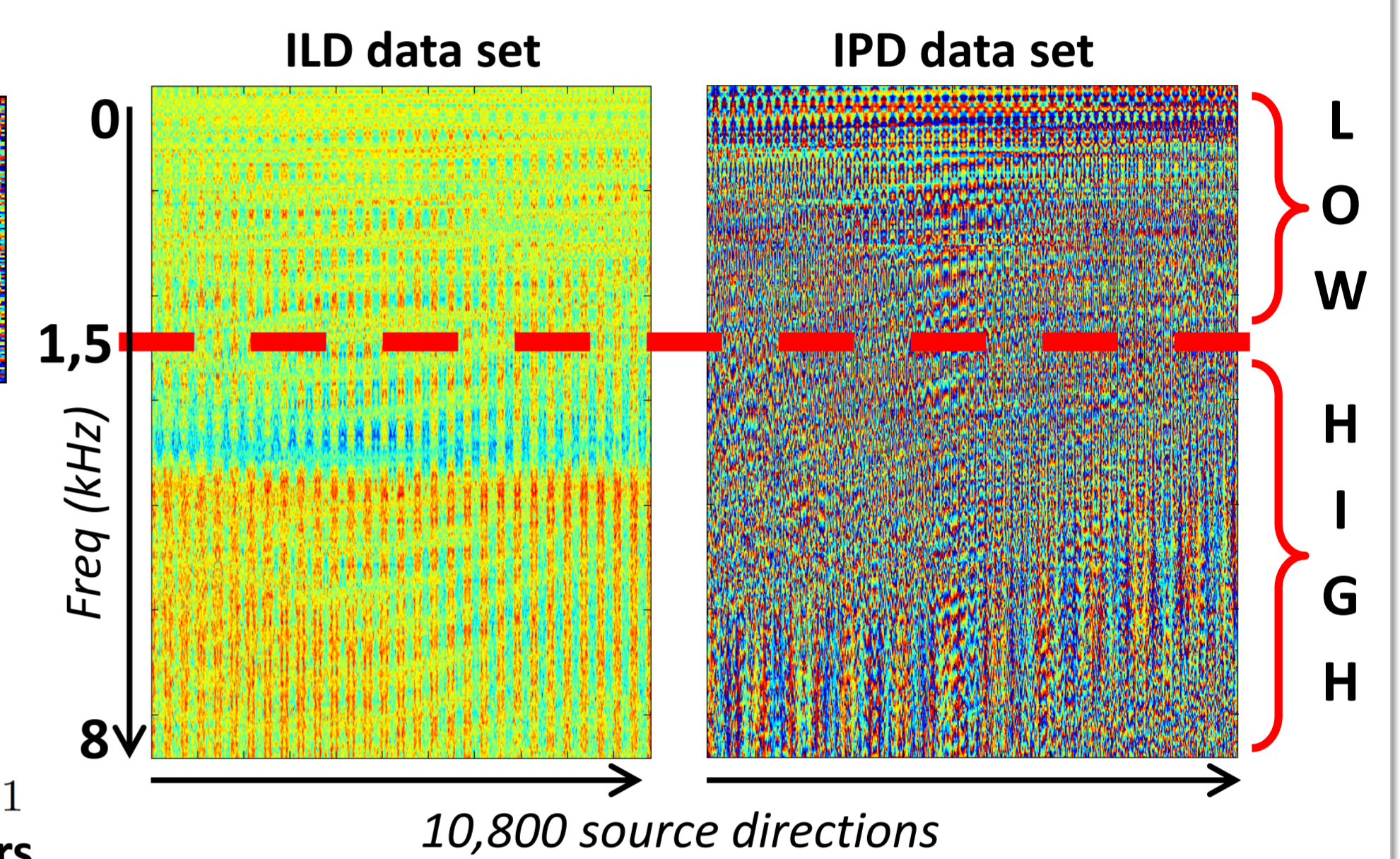
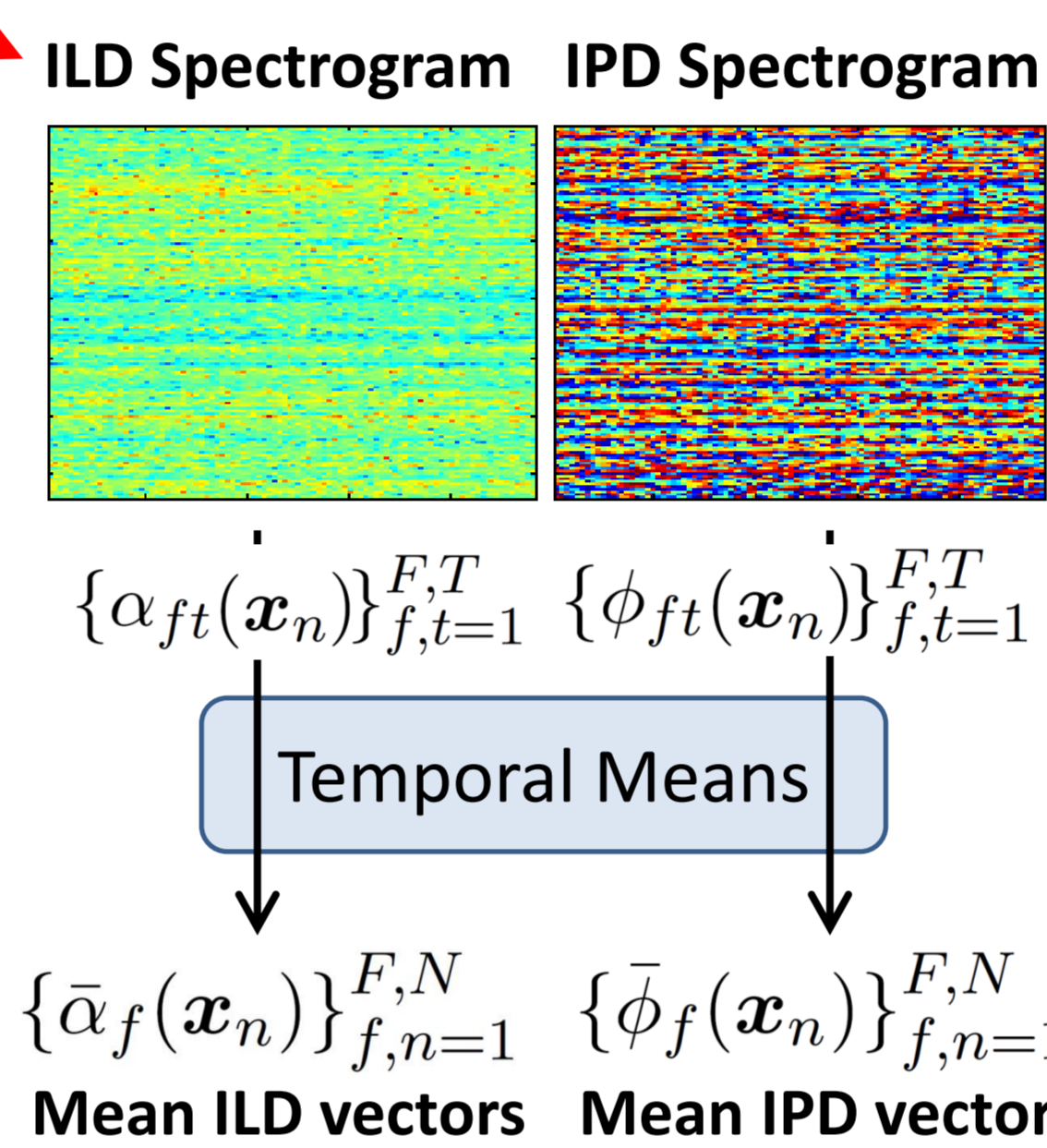
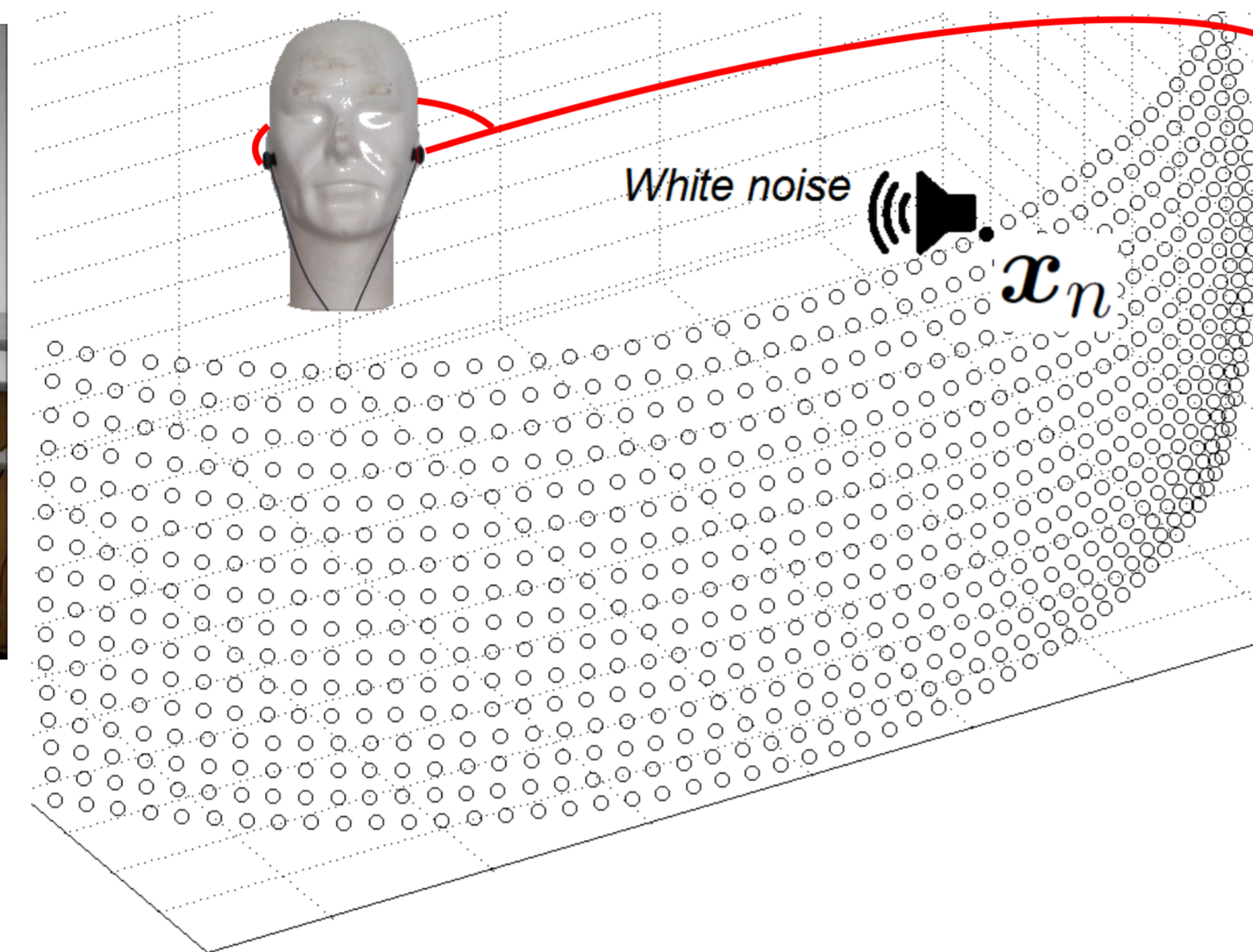
## Challenges Addressed

- Can we use spectral interaural cues for accurate 2D sound source localization?
- How to obtain a mapping function from cues to direction using a real world complex system with filtering effects?
- How to deal with the spectral sparsity of real world sounds such as speech?

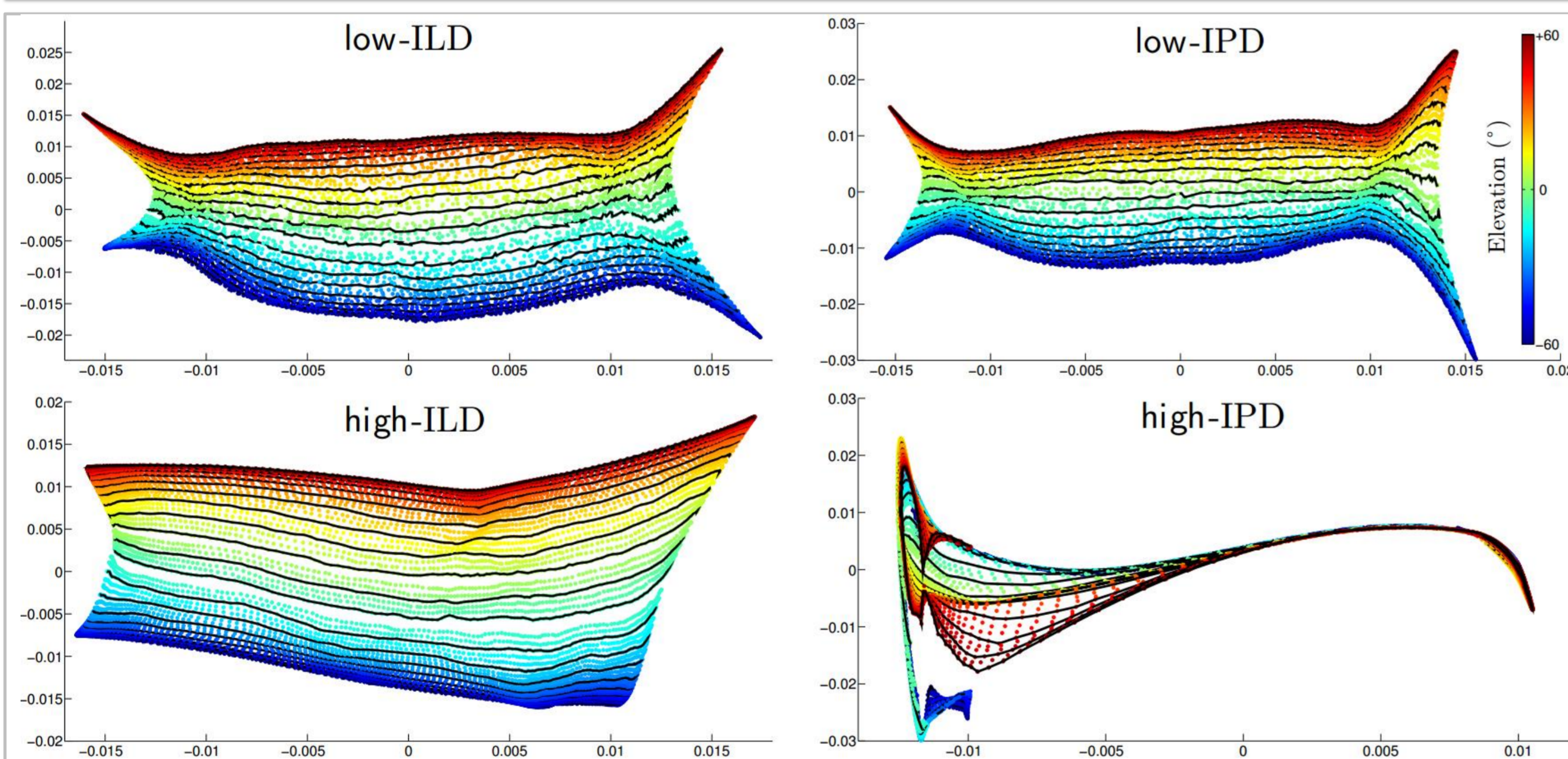
## An Audio-Motor Sound Database



- 10,800 motor states
- 180 azimuth, 60 elevations, 2° steps
- White noise + rnd speech from TIMIT
- Data available online\*\*



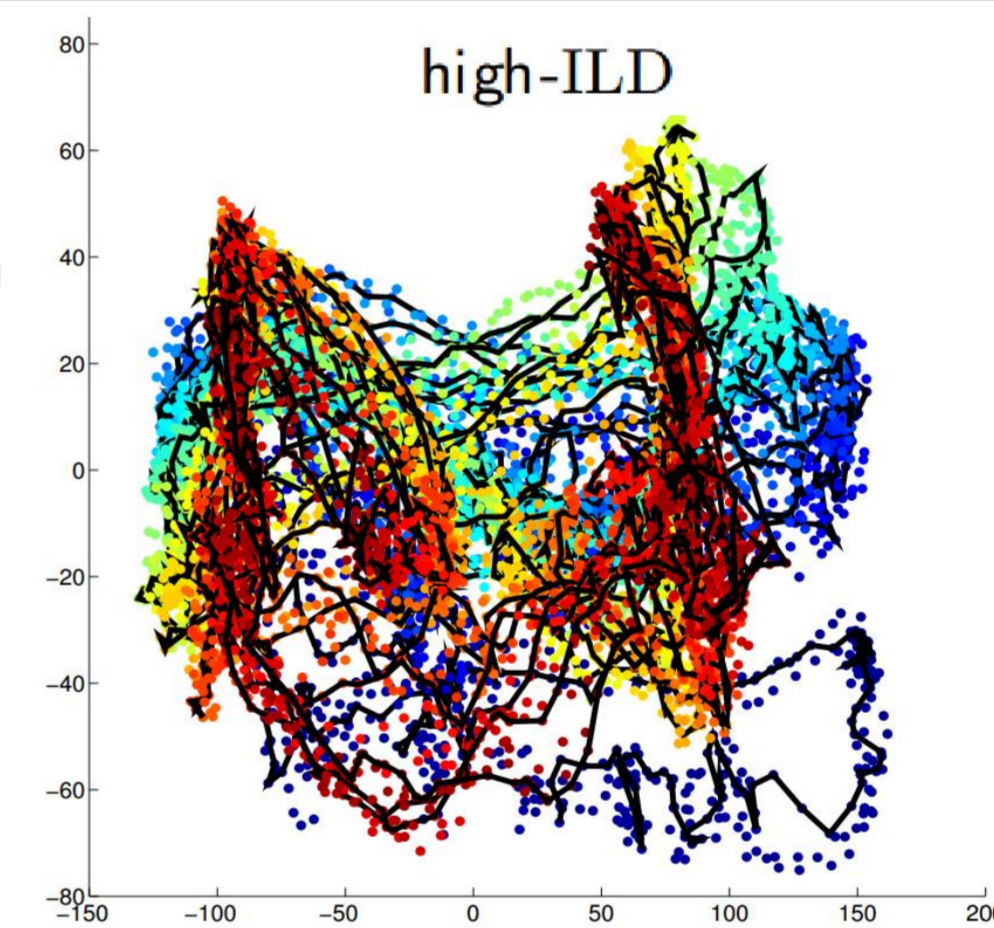
## Intrinsic Manifold Structure of Spectral Interaural Data



• Non linear dimensionality reduction on interaural data sets using the local tangent space alignment (L TSA) algorithm (Zhang & Zha, 2003)

• The smoothness of low-ILD, high-ILD and high-IPD representations shows the existence of an intrinsic manifold structure of spectral interaural data and of a homeomorphism between 2D sound source direction and these cues

• Ambiguities in high-IPD cues confirming the Duplex theory

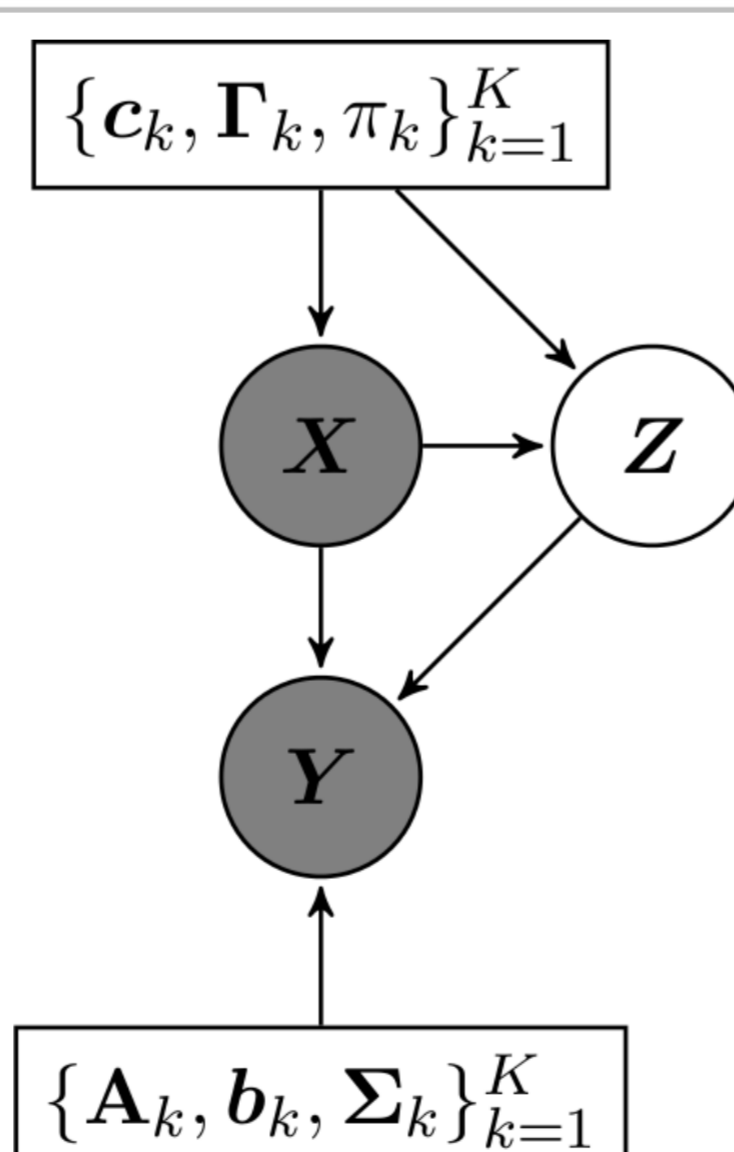
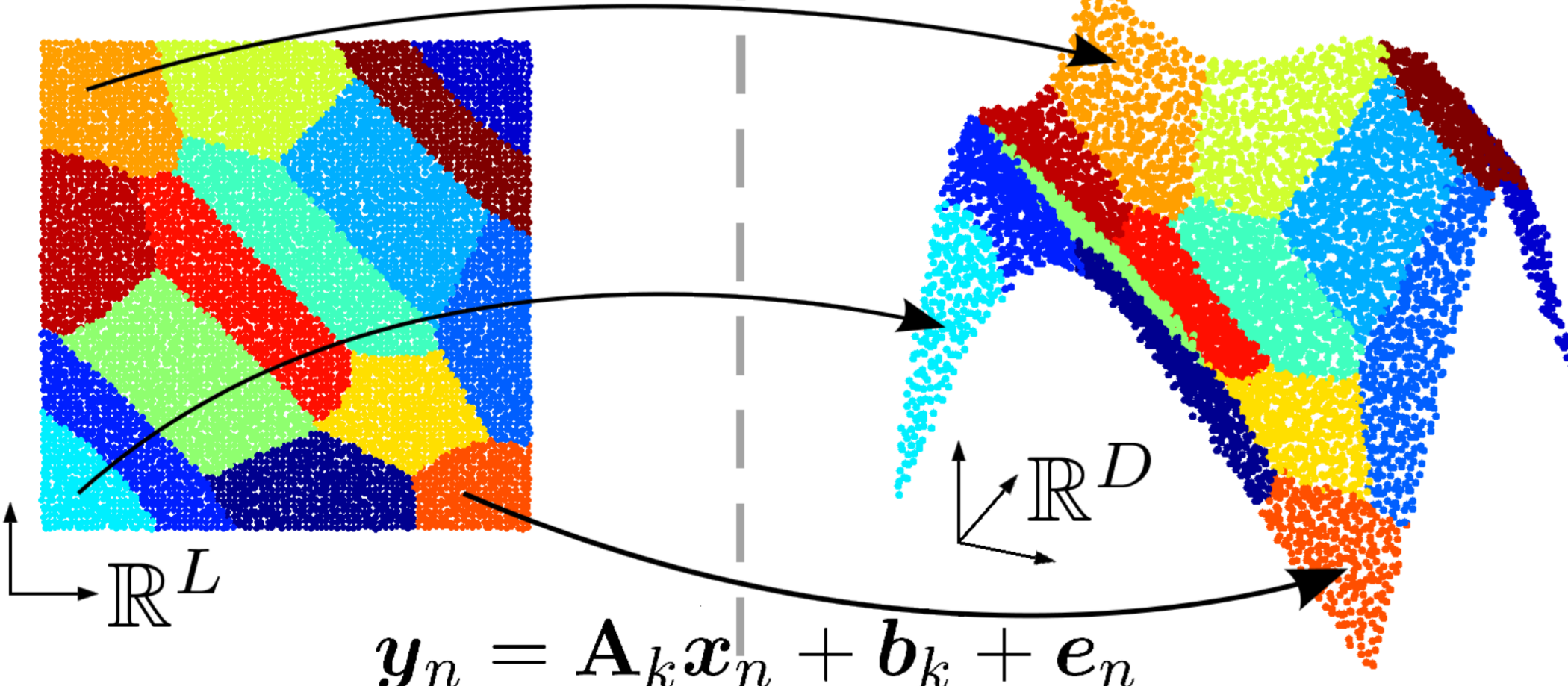


- Linear dimensionality reduction with principal component Analysis (PCA)
- Emphasizes the highly non-linear structure of interaural cues and the complexity of their relation to 2D sound source positions

Need for a locally linear mapping learning technique to perform accurate 2D sound source localization from spectral interaural cues

## Probabilistic Piecewise Affine Regression (PPAR) - Learning

$\{\mathbf{x}_n\}_{n=1}^N$  Source positions  $\{\mathbf{y}_n\}_{n=1}^N$  Interaural cues



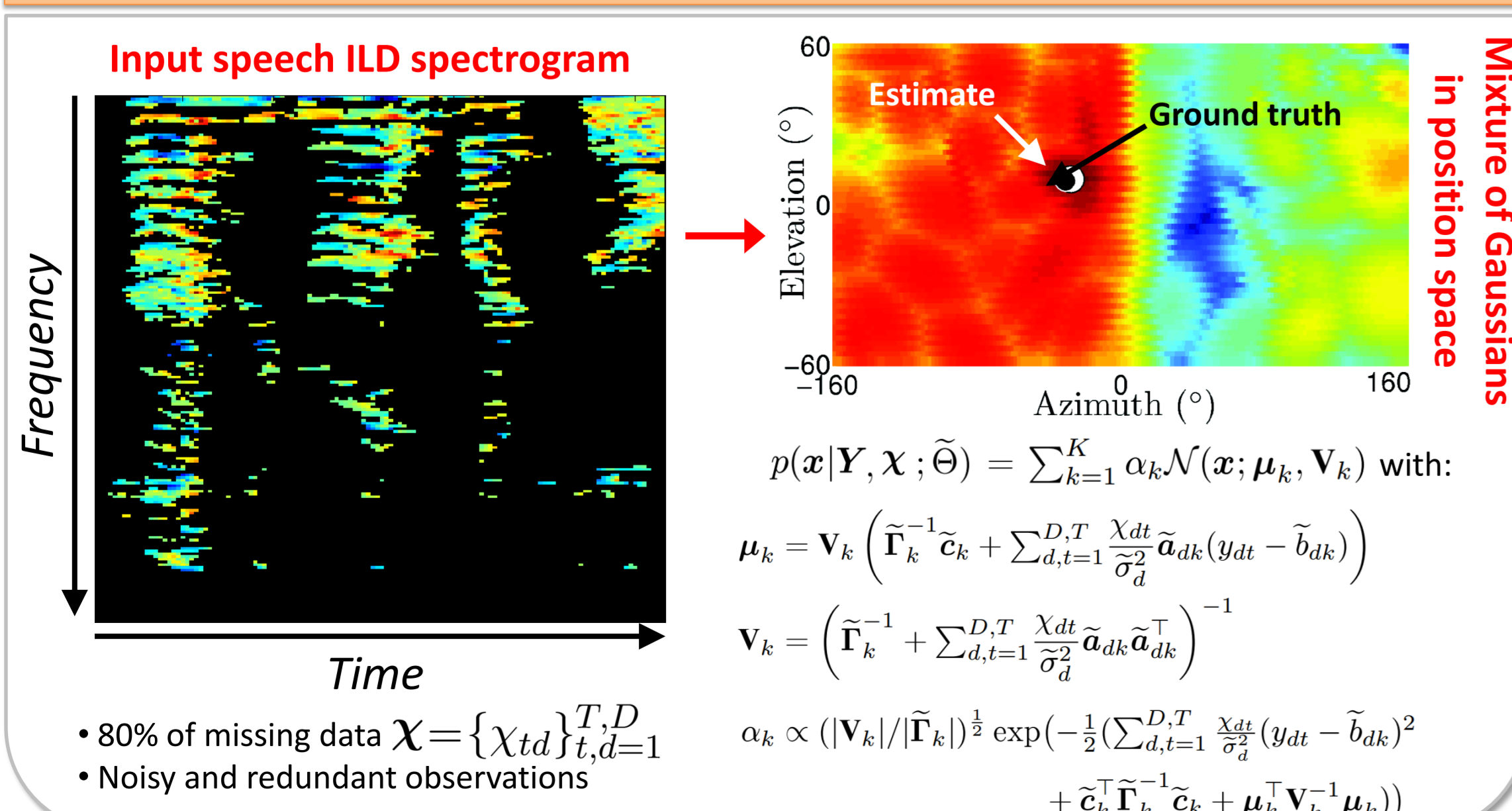
$$p(\mathbf{y}_n | z_{kn} = 1, \mathbf{x}_n; \Theta) = \mathcal{N}(\mathbf{y}_n; \mathbf{A}_k \mathbf{x}_n + \mathbf{b}_k, \mathbf{\Sigma})$$

$$p(z_{kn} = 1 | \mathbf{x}_n; \Theta) = \frac{\pi_k \mathcal{N}(\mathbf{x}_n; \mathbf{c}_k, \mathbf{\Gamma}_k)}{\sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}_n; \mathbf{c}_k, \mathbf{\Gamma}_k)}$$

$$p(\mathbf{x}_n; \Theta) = \sum_{k=1}^K \pi_k \mathcal{N}(\mathbf{x}_n; \mathbf{c}_k, \mathbf{\Gamma}_k)$$

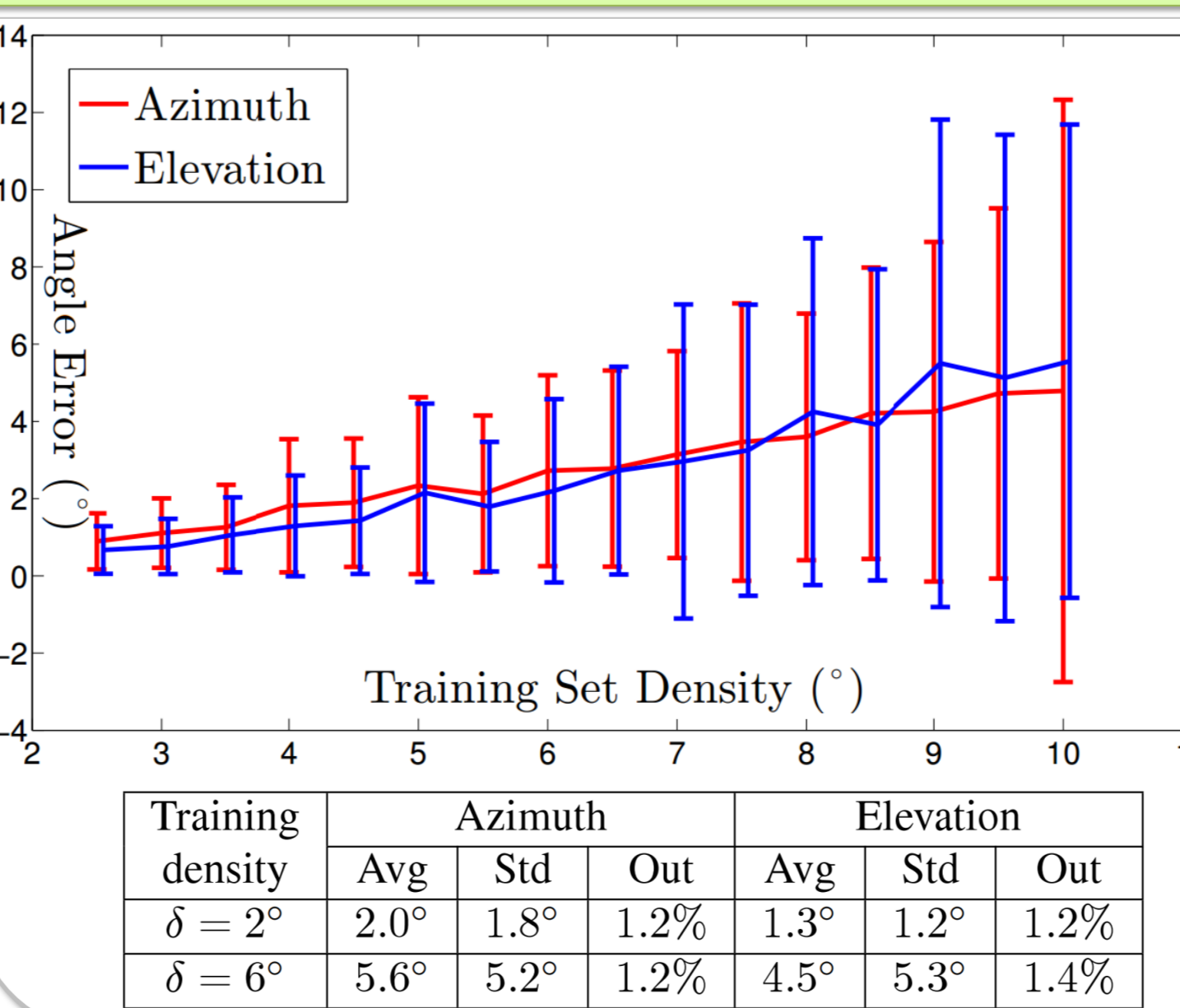
Maximum likelihood estimation of  $\Theta$  with a closed form EM algorithm

## PPAR - Spectrogram Inversion



- 80% of missing data  $\mathbf{X} = \{\chi_{td}\}_{t,d=1}^{T,D}$
- Noisy and redundant observations

## Results



• Average and standard deviation of angular errors in white noise localization as a function of the training set's density.

• Localization results with real world speech recordings

## Conclusion

- A general framework to study and map together data presenting a non-linear manifold structure
- Insights on the richness of interaural spectral cues for 2D sound localization

## Future work

- Localization of multiple sound sources using mixed inverse PPAR models
- Robustness to reverberations